

Research Article

Social Media and Employee Performance: Employee Engagement and Task Completion as Mechanisms Connecting Social Media to Performance

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Abstract: This study examines the complex relationship between workplace social media usage and employee performance through testing employee engagement and task completions as parallel mediators while also assessing whether employee engagement moderates the social media usage and employee performance relationship. Moving beyond the common “beneficial versus harmful” debate the study adopts a mechanism-based perspective grounded primarily in the Job Demands-Resources model and Social Exchange Theory. A cross-sectional quantitative survey was conducted among teaching and non-teaching employees of higher education institutions in Punjab, India, yielding 707 valid responses. Confirmatory factor analysis demonstrated strong reliability and convergent validity for all constructs with excellent measurement model fit. Structural equation modelling results showed that social media usage was positively associated with employee engagement and tasks completed. Both employee engagement and tasks completed are positively predicted performance of the employees at HEIs. However, High social media usage retained a significant negative direct effect on employee performance. Bootstrapped mediation analyses revealed significant positive indirect effects through employee engagement with a positive total indirect effect indicating competitive (inconsistent) mediation. In contrast, the interaction was not significant suggesting that employee engagement functions as a mediator and direct predictor but not as a moderator. The findings highlight social media’s dual role in organizations, it can enhance performance through engagement and task execution while simultaneously undermining performance via direct disruptive effects. These results support balanced, role-sensitive social media policies in higher education institutions.

Keywords: Workplace social media usage, Employee performance, Employee engagement; Task completion, Mediation, Moderation; Structural equation modelling, Higher education institutions.

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INTRODUCTION

Over the last decade, social media has moved from being a purely personal communication tool to becoming a routine part of organizational life (Auxier & Anderson, 2021). Employees now regularly use social media platforms to exchange information and coordinate work and stay connected (Sarah Chanu, 2025). This shift has been accelerated by remote and hybrid work where digital communication is not just convenient but it’s necessary (Mohiya, 2025). As a result, social media use is no longer an “outside-of-work” activity it has now increasingly overlapped with all work processes (Karimi et al., 2024).

At the same time, research and organizational opinion remain divided on whether social media ultimately benefits or harms employee outcomes (Landers & Callan, 2014; MA et al., 2022). From a performance perspective social media can and does support faster information sharing (Sivakumar et al., 2023), it reduces communication barriers (M. Ahmad et al., 2024) and creates informal channels for problem-solving. However, an opposing perspective emphasizes the counterproductive potential of social media in work settings (Eliyana et al., 2020; Sharma et al., 2020). Critics argue that frequent social media use can distract employees (Wei et al., 2024), fragment attention and reduce deep focus, especially when usage is unrelated to work tasks. Notifications (Ohly & Bastin, 2023), constant connectivity (Tandon et al., 2021)

and the habitual checking of feeds can interrupt task flow and lower efficiency (Jong et al., 2021). Over time this can lead to delays in task completion (Ohly & Bastin, 2023) reduced quality of work (Damayanti, 2023) and increased cognitive fatigue (Upshaw et al., 2022). Some organizations therefore treat social media primarily as a source of productivity loss, emphasizing control and restriction rather than integration.

Therefore, understanding social media in organizations requires moving beyond the simple question of whether it is “good” or “bad.” A more meaningful approach is to examine how and why social media influences performance. This includes considering the behavioural pathways through which social media shapes day-to-day work outcomes such as the ability to complete tasks effectively. As well as psychological pathways such as employee engagement by focusing on these mechanisms the relationship between social media use and employee performance can be explained more clearly.

The growing evidence suggests that social media has become a normal feature of digitally enabled workplaces (Chatterjee et al., 2023; Mohiya, 2025) this study aims to move beyond the simple debate of whether social media is “helpful” or “harmful” by explaining the mechanisms through which social media usage may influence employee performance. Prior research suggests that workplace social media use is linked to employee outcomes, but the direction and magnitude of effects vary across settings and forms of use, implying that how the effect occurs matters. Accordingly, the study pursues the following objectives

- To assess the direct relationship between Social Media Usage (SMU) and Employee Performance (EP).
- To examine whether SMU influences Employee Engagement (EE) and Task Completion (TC).
- To test Employee Engagement and Task Completion as parallel mediating mechanisms explaining how SMU translates into performance outcomes.
- To evaluate whether Employee Engagement functions as a boundary condition (moderator) that changes the strength or direction of the Social Media Usage and Employee Performance alongside its role as a mediator.

This paper is structured as follows. Section 2 reviews the relevant literature on workplace social media usage, employee engagement, task completion and employee performance and then develops the study hypotheses and conceptual model. Section 3 describes the research design, sampling approach, measurement of constructs and the analytical procedures used for confirmatory factor analysis (CFA) and structural equation modelling (SEM). Section 4 presents the empirical findings, including descriptive statistics, measurement model assessment (reliability and validity), hypothesis testing for direct effects and the evaluation of parallel mediation and moderation effects using SEM outputs. Section 5 discusses the results in relation to prior research, highlighting theoretical and practical implications and explaining unexpected patterns where relevant. Finally, Section 6 concludes the study by summarizing key contributions, outlining limitations and suggesting directions for future research.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

This section reviews theory and prior empirical findings on social media use in organizations, employee engagement, task completion and performance. We identify dual pathways linking social media to performance, a psychological pathway via engagement and a behavioural pathway via task execution and develop hypotheses. We begin by outlining theoretical foundations then the links between social media usage, employee engagement and task completion are discussed. We then review the engagement performance and task completion-performance relationships. Finally, we justify parallel mediation by engagement and task completion, discuss the rationale for an engagement moderation and state testable hypotheses.

Theoretical Foundations

We draw primarily on the Job Demands-Resources (JD-R) model (Bakker & Demerouti, 2007; Scholze & Hecker, 2024) and Social Exchange Theory (SET) (R. Ahmad et al., 2023) with supplementary perspectives on attention/distraction and self-regulation. The JD-R model frames work contexts as comprising job demands aspects that deplete energy and resources aspects that motivate and support performance (Scholze & Hecker, 2024). In the digital age, social media use represents both potential resources such as rapid information sharing, social support, knowledge exchange and demands such as constant connectivity, interruptions (Koessmeier & Büttner, 2021; Scholze & Hecker, 2024). SET emphasizes reciprocal dynamics when employers provide resources information support using social media. Employees feel obliged to repay through positive work attitudes and behaviours (Mohiya, 2025). In practice, SM platforms can be viewed as organizational resources informational and relational capital that under SET elicit employee engagement and extra effort as payback (Kasim et al., 2022).

From an attention and self-regulation standpoint, social media cues (notifications) compete for limited cognitive resources. Distraction theory argues that SMU can draw attention away from tasks, impairing performance (Koessmeier & Büttner, 2021). Self-regulation theory suggests that individual differences willpower determine how well a person controls such impulses (Aragoncillo & Orus, 2018). Thus, SMU’s net effect depends on a balance between its resource-enriching value aiding work via faster info flow & social support and its demand-creating value consuming attention & self-control (Wei et al., 2024). We will test this dual-nature hypothesis by considering SMU’s positive pathways (resources) and negative

pathways (demands) in parallel.

Social Media Usage and Employee Engagement

Workplace social media use both enterprise platforms and public sites can enhance social capital and connectivity among colleagues. Facilitating network ties, shared vision and trust, SMU provides resources that stimulate employee's psychological investment in work. Several recent studies report that SMU is positively linked to employee engagement: for example, internal social media use creates open communication and voice, which drives engagement. In an empirical study of Chinese tech firms, (MA et al., 2022) found that work-based SMU increased work engagement via resource gains which in turn boosted task performance. Likewise, (Kasim et al., 2022) showed that SMU improves job resources specifically social capital thereby raising work engagement. (Yen et al., 2020) and van (Pekkala & van Zoonen, 2022) similarly report that SMU can foster engagement by keeping employees connected and informed. In JD-R terms SMU functions as a job resource that meets social and cognitive needs energizing employees

From a SET perspective accessing organizational support via SM quick help on a problem gives employees resources to reciprocate with greater commitment and enthusiasm. For example, (Scholze & Hecker, 2024) argue that SMU by increasing perceived support and satisfaction trigger a reciprocal boost in engagement. Thus, we theorize that higher SMU will associate with higher employee engagement. We note, however, that some studies caution excessive personal SMU can also drain engagement if it symbolizes escape from work but by focusing on work-related SMU, we expect the resource perspective to dominate

Social Media Usage and Task Completion

Social media use can also affect employees task completion their ability to efficiently finish assigned work. On one hand, SMU can provide informational and coordination resources that help in task execution. Enterprise social platforms allow quick clarifications, file sharing and coordination updates, which may shorten task cycles. (Sun et al., 2020) found that complementary use of work-oriented (DingTalk) and social-oriented (WeChat) SM enhanced task performance by providing both instrumental support and emotional support (Song et al., 2019). Similarly, accessing organizational knowledge via SM can streamline problem-solving potentially accelerating task completion. In JD-R terms, SMU here is a job resource that facilitates goal achievement. On the other hand SMU can create digital interruptions. Each notification or chat pings interrupts the flow of focused work (Koessmeier & Büttner, 2021; Wei et al., 2024). Research shows that such distractions deplete cognitive capacity: social media cues can pull attention away from tasks, resulting in attention residue and slower task progress. (Jiang, 2021) note that excessive SMU distracts users and reduces the level of employee performance. Therefore, SMU → TC is ambivalent. If SM is used in a task-focused way for project coordination it should enhance task completion. If SM is used mainly for social browsing during work it will impair task completion. Based on JD-R we expect the resource-benefits to generally outweigh distraction costs when use is job-related so our hypothesis assumes a positive association.

Employee Engagement and Employee Performance

Work engagement is well-established as a key predictor of employee performance (Benn et al., 2015; Corbeanu & Iliescu, 2023). Engaged employees invest more energy and proactivity in tasks yielding both better task performance in terms of efficiency, quality of core duties and broader job dedication. Meta-analyses and reviews consistently find a moderate-to-large positive correlation between engagement and performance (Zahrah et al., 2017). For instance, (Neuber et al., 2022) reported a pooled correlation of about .48 between work engagement and task performance. Engaged employees are positive and enthusiastic about their work and are willing to expend discretionary effort which translates into higher productivity (Kasim et al., 2022). Engagement brings sustained vigour and dedication, which in turn produce better outcomes such as creativity and innovation. Thus, consistent with JD-R, engagement itself is a personal resource that amplifies performance. We thus expect EE → EP to be strongly positive.

Task Completion and Employee Performance

Task completion is conceptually a component of performance (van Zyl et al., 2024). Employees who finish tasks fully and on time are by definition performing effectively. In multi-dimensional performance models, "task performance" is one of the core dimensions of overall job performance (along with contextual behaviours. Better task completion accurately and promptly finishing assigned work directly raises productivity (Ohly & Bastin, 2023). The structural analysis in Zhao et al. (2021) found that work engagement raised task performance and job dedication suggesting a chain SMU→EE→EP . In our model, we treat task completion as a mediator where employees who complete work more efficiently will register higher performance ratings . While we are not aware of direct tests of SMU→TC→EP, the logic is straightforward any mechanism that improves task execution such as coordination via SM or that impairs it such as distraction will ultimately affect performance. We therefore expect TC → EP to be positive more effective task completion translates into higher performance scores.

Rationale of Parallel Mediation

We propose that SMU affects performance indirectly through two simultaneous pathways. First, SMU can boost

engagement (as argued in 3.2) and engagement in turn raises performance (as argued in 3.4). Second, SMU can influence how well employees complete tasks (as argued in 3.3) and better task completion raises performance (3.5). These are parallel mediators because engagement a psychological investment and task completion behavioural represent distinct but co-occurring processes. This approach follows recent calls to unpack SMU and performance links rather than treat them as net effects. For example, Zhao et al. (2021) found that SMU raised engagement and reduced interruptions both of which influenced task performance. In JD-R terms, SMU adds resources via social capital and communication which enhances engagement and thereby performance. While separately it provides performance related information and coordination that aid task completion. However, SMU also imposes demands attention costs that may diminish task completion (Kasim et al., 2022). Estimating both mediators together we can capture a competitive mediation effect one pathway (engagement) may drive performance up while distraction via task delays may drive it down potentially offsetting each other. A bootstrapped SEM will allow us to quantify these indirect effects.

Rationale of Moderation

We also consider whether employee engagement moderates the SMU → performance link. High engagement might change how SMU translates into performance. On the one hand, engaged employees may leverage SM more productively using it strategically for work coordination and be less susceptible to distraction. In this view, engagement buffers the negative attentional costs of SMU making the SMU→EP link more positive or at-least less negative at high EE. On the other hand, one could argue engaged employees are already resource-rich so additional SMU yields diminishing returns; however, our expectation by default is a positive moderating effect the benefit pathway via engagement should strengthen the SMU→EP association for highly engaged individuals. While low-engagement employees might squander SM opportunities or suffer more from interruptions. This reasoning aligns with COR theory (Halbesleben et al., 2014) ideas that resources co-occur in caravans engaged employees have more resources to invest in converting SMU into performance gains. We will test whether the SMU→EP slope differs by EE.

Conceptual Framework and Hypotheses Summary

The proposed conceptual model figure 1 explains employee performance as a function of social media usage through both direct and indirect pathways. Specifically, SMU is hypothesized to influence EP directly while also affecting EP indirectly through two parallel mediators. Employee engagement captures the motivational pathway and the task completion captures the behavioral pathway. In addition, the model assigns EE a dual role by testing it not only as a mediator but also as a moderator of the SMU→EP relationship through the interaction term (SMU × EE), allowing the study to examine whether engagement changes the strength of SMU’s effect on performance. This structure is analytically useful because it captures the possibility that social media may simultaneously generate performance-enhancing mechanisms via engagement and task completion while also retaining a separate direct effect on performance.

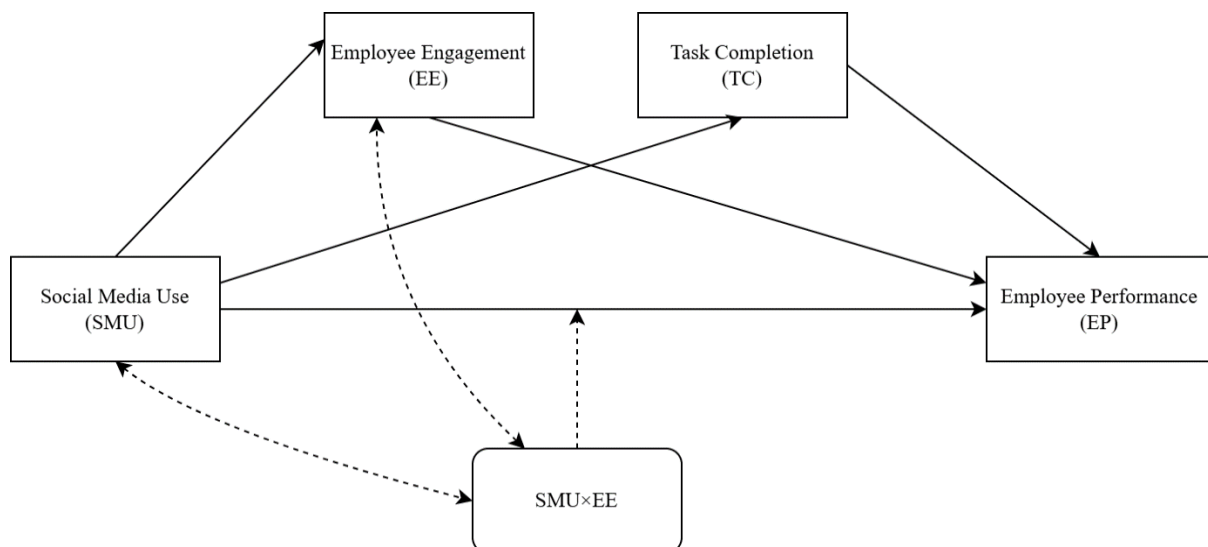


Figure 1: Conceptual model used in the paper to study effects of SMU through EE and TC on EP

Employee Engagement is modelled as both a mediator and a moderator to test whether it explains the SMU-EP relationship and whether it changes the strength of that relationship The hypothesis used in the study can be formulated as

Direct Paths

- H1. Social media usage significantly influences with greater employee engagement.
- H2. Social media usage significantly influences task completions by employees in HEIs.
- H3. Employee engagement significantly influences employee performance in HEIs.
- H4. Task-completions significantly influence employee performance.

- H5. Social media usage significantly influences employee performance.

Parallel mediation

- H6. Employee engagement mediates the relationship between social media usage and employee performance.
- H7. Task completion mediates the relationship between social media usage and employee performance.
- H8. Employee engagement and task completion jointly mediate the relationship between social media usage and employee performance.

Moderation effects

- H9. Employee engagement moderates the relationship between social media usage and employee performance.

Research Design

This study uses a quantitative cross-sectional design based on a multi-site survey of higher education institutions (HEIs) in Punjab, India. It is guided by a theory-driven mediation and moderation framework. The conceptual model positions social media usage as the antecedent of employee performance operating through two parallel mediators employee engagement and task completion with employee engagement also moderating the social media usage and employee performance relationship through latent interaction effects.

Sampling Procedure and Target Population

The target population consisted of employees of HEIs in Punjab, India, including both teaching and non-teaching staff. To ensure geographic and institutional heterogeneity multi-stage region sector sampling strategy was used. Stages are defined as

- Stage 1: Punjab was divided into its three administrative regions: Malwa, Majha and Doaba.
- Stage 2: Within each region, one public and one private HEI were selected.
- Stage 3: Eligible employees from 6 HEIs participated, covering both academic and administrative units.

For the survey the Inclusion criteria for employees was

Eligible participants were current teaching and non-teaching employees working in the participating HEIs in Punjab, India. To ensure adequate exposure to the institutional environment respondents were required to have completed at least six months of continuous service and they must be of 18 years of age or older and have completed minimum of 20 work hours per week. In addition, only those employees who provided informed consent and submitted analysable responses on the focal constructs. Also no more than 20% missing responses per scale after data screening were retained for analysis.

Sample size planning

The study was planned as a large-N design to support stable estimation of a moderately complex SEM with 30 observed indicators (SMU = 13, EE = 6, TC = 6, EP = 5) two parallel mediators and latent interactions (SMU × EE). This was intended to ensure adequate statistical power for: detecting small-to-moderate structural paths estimating bias-corrected bootstrapped indirect effects in a parallel-mediation model and detecting latent interaction (moderation) effects

We targeted power $\geq .80$ ($\alpha = .05$, two-tailed) to detect standardized path coefficients in the range of approximately $\beta = .15-.20$, as well as small indirect effects under realistic measurement conditions. For moderation, planning assumed a small incremental effect for the latent product term SMU × EE, which typically requires a large sample for stable estimation.

A second practical rationale was the breadth of the overall study. Although the present analysis uses only a subset of constructs, the full questionnaire contained 66 items, designed to examine additional pathways through which social media usage may affect employee performance. For scale development and factor-analytic designs, widely cited heuristics recommend 10 respondents per item, implying a minimum of approximately 660 responses. The achieved sample exceeded this threshold ($66 \times 10 = 660$) with a total N = 707.

Data collection and Ethics

Data were collected using a structured, self-administered questionnaire hosted on Google Forms. The survey link was distributed through institutional channels at the selected HEIs. To improve response rates and reduce nonresponse bias, two reminder emails were sent at reasonable intervals.

Participation was fully voluntary and anonymous. A detailed consent statement appeared on the opening page, describing the study purpose, expected completion time (approximately 16 minutes) and contact information for queries. Proceeding to the survey required informed consent and participants were explicitly informed of their right to withdraw at any point prior to submission. No personally identifying information was collected beyond basic demographics. All procedures complied with ethical guidelines for research involving human participants. Data were stored on restricted-access drives and only de-identified files were used for analysis.

Achieved sample and response rate

During the data collection period (June 1-September 30, 2025), a total of 2,415 invitations were distributed across the six participating HEIs. We received 860 submissions, yielding a gross response rate of 35.6%. After applying the a priori data-quality screening criteria (consent and eligibility, ≤ 20% missingness per scale, attention checks, consistency checks and implausible completion-time flags), 707 responses were retained for analysis. This corresponds to an overall valid rate of 29.3% relative to invitations (707/2,415) and a usable rate of 82.2% relative to submissions (707/860). Because the valid response rate was 29.3%, non-response bias was examined by comparing early and late respondents on the focal variables and key demographic characteristics. The comparisons showed no statistically significant and practically meaningful differences, suggesting that systematic non-response bias is unlikely to materially distort the results.

Sample Characteristics and Demographics

The final analytic sample comprised N = 707 employees drawn from six HEIs in Punjab (three public and three private) distributed where

- Role composition of teaching = 467 (68%) and non-teaching = 240 (32%)
- Gender distribution with females = 319 (45.1%) and males = 388 (54.9%)

This multi-site region-sector coverage introduces heterogeneity in governance of public and private HEIs and job their function be it academic or administrative which enhances the external validity of inferences for the HEI workforce in the state. Descriptive statistics for the focal constructs indicate moderate levels of social media use and distractions, along with lower self-rated performance in Table 1.

Measurement of Constructs

All constructs used in the study are modelled as reflective latent variables estimated with CFA prior to the structural tests. Items used five-point Likert scale anchored in 1 = strongly disagree to 5 = strongly agree and frequency stems 1 = never to 5 = very often. Items were coded so higher scores = more of the construct. Table 1 presents the constructs and the scales used .

Table 1:Key Scales and studies and adaptation rationale

Construct	Scale	Adaptation Rationale
Social-Media Usage (General)	Social Media Use Scale - SMUS (Tuck & Thompson, 2024) Short Internet Addiction Test-SNS version (Wegmann et al., 2015) s-IAT-SNS (Valenti et al., 2025)	SMUS items capture frequency, duration and multi-platform breadth; s-IAT-SNS contributes compulsive-use symptoms for discriminant validity.
Social-media usage (problematic)	Bergen Social Media Addiction Scale (BSMAS) - 6 items, 5-point Likert (Gomez et al., 2024) (Zarate et al., 2023) cross-culturally validated	Adds problematic-use which complements frequency-based SMUS items useful for testing U-shaped SM & performance.
Social-Media at Work	Work-related Social Media Questionnaire WSMQ (Landers & Callan, 2014)	Studied both Harmful and Positive impact of SM in workplace
	Social-Media Use for Work (SMUW) (Koessmeier & Büttner, 2021; Leftheriotis & Giannakos, 2014) Workplace Social Media Usage Scale (Celebi et al., 2022)	Focuses on instrumental use knowledge sharing aligning with “employee performance” Distinguishes passive browsing vs active content creation, matching recent findings that motive moderates performance impact (Ononye et al., 2023).
	Job-Related Social-Media Scale (Marengo et al., 2020) - distinguishes content creation, networking, entertainment	Helps test whether <i>active</i> (posting) versus <i>passive</i> (scrolling) use moderates the SM to performance link.
Task Completion	Task-Performance sub-scale of the Individual Work Performance Questionnaire (IWPQ; Koopmans et al., 2013) + positive-phrased items from Ali-Hassan et al. (2015)	Provides a direct behavioural output metric that precedes overall performance.

	Williams & Anderson Task-Performance subscale (1991) (Williams & Anderson, 1991) 7 items; supervisor-rated option	Offers behavioural language suited to academic and administrative roles (“adequately completes assigned duties”).
Employee Engagement	ISA Engagement Scale (Soane et al., 2012) - vigour, dedication, absorption JRA Engagement Scale (Benn et al., 2015) - affective commitment	Dual source increases content coverage and allows second-order modelling (cognitive vs emotional engagement).
	Utrecht Work Engagement Scale (UWES-9 / UWES-17) vigour, dedication, absorption (Schaufeli et al., 2006)	International benchmark; allows comparisons with meta-analytic norms and links directly to performance outcomes.
Work Performance	IWPQ (Benn et al., 2015) Work-Performance (WP) scale (Leftheriotis & Giannakos, 2014) Digital-era performance items (Oksa et al., 2022)	Captures both self-rated efficiency and quality of output; prior studies (Gallup, 2024; Khan et al., 2020) confirm strong convergence with supervisor ratings.
	WHO Health & Work Performance Questionnaire (HPQ) - self-reported performance loss & absolute output (Kessler et al., 2003; Lysandra et al., 2023)	Frequently used in cross-industry studies; can validate IWPQ findings and translate into cost-of-distraction estimates.

Social Media Use (SMU)

SMU indexes intensity and breadth of use during work with content drawn from the SMUS (frequency, duration, multi-platform breadth) (Tuck & Thompson, 2024) and selected problematic-use symptoms adapted from s-IAT-SNS (Valenti et al., 2025) and BSMAS (Gomez et al., 2024) to strengthen discriminant validity against work performance. Wording was harmonized to the work context (adding “during working hours or at work”). In total 13 items were selected for SMU. Items for Workplace related SMU was adapted from WSMUS (Celebi et al., 2022).

Task Completion

Task completion denotes the timely and accurate fulfilment of role-prescribed duties from grading exam scripts to processing payroll batches. Whereas project-management research typically measures completion via earned-value metrics, industrial-organisational psychology treats it as the behavioural core of task performance (Koopmans et al., 2013). Recent validation studies confirm that higher task-completion proficiency predicts downstream outcomes such as course-pass rates and administrative turnaround (van Zyl et al., 2024). Interrupt-driven SM usage could elongate completion cycles, raising error rates and backlog.

Employee engagement

Employee engagement is a positive fulfilling work-related state of mind characterised by vigour, dedication and absorption” (Mauno et al., 2007; Schaufeli et al., 2002) Rooted in the Job Demands-Resources model (Bakker & Demerouti, 2007), engagement captures the motivational energy an employee invests in discretionary effort, innovation and organisational citizenship. Longitudinal meta-analyses show that units in the top quartile of engagement report 21% higher profitability and 17% higher productivity than bottom-quartile peers (Gallup Inc, 2023). Social media can nurture engagement using community building and professional recognition. However, Social media can also precipitate engagement erosion as its overuse fuels fatigue and even social comparison among employees.

Employee Performance (EP)

EP reflects the self-rated task efficiency and output quality using items adapted from the IWPQ (Benn et al., 2015) related to Work-Performance Scale (Leftheriotis & Giannakos, 2014) its anchors align with recent digital-era performance wording. Higher scores indicate better performance of the employees. Final item counts per construct and summary statistics are presented with reliability validity results in Table 3.

RESULTS OF ANALYSIS

This section presents the empirical findings of the study and evaluates the proposed measurement and structural models. The section begins with the assessment of reliability and validity, followed by hypothesis testing for direct, mediating, and moderating effects using structural equation modelling.

Constructs Descriptive and Correlations

The descriptive statistics and bivariate correlations among the study variables are presented in Table 2. The mean scores

indicate that respondents reported relatively moderate levels of social media usage (SMU M = 3.69, SD = 1.03) and TC (M = 3.35, SD = 1.09) while employee engagement (EE M = 3.32, SD = 1.12) and employee performance (EP M = 3.30, SD = 1.10) were also at moderate levels. The standard deviations (ranging from 0.97 to 1.12) suggest adequate variability in responses across all constructs.

Table 2: Constructs, observations, descriptive and inter-construct correlations

Variable	k (items)	M	SD	1	2	3	4
1. SMU	13	3.69	1.03	1.00			
2. EE	6	3.32	1.12	0.23***	1.00		
3. TC	6	3.35	1.09	0.19***	0.04	1.00	
4. EP	5	3.30	1.10	-0.24***	0.21***	0.21***	1.00

Note. SMU = Social Media Usage; EE = Employee Engagement; TC = Task Completion; EP = Employee Performance. ***p < .001; ns = non-significant.

The correlation analysis reveals several significant associations in the expected directions. SMU is positively correlated with EE (r = 0.23, p < .001) and TC (r = 0.19, p < .001), suggesting Meaning higher social media usage is associated with slightly higher employee engagement and task completion. In contrast, SMU is negatively correlated with EP (r = -0.24, p < .001) at the bivariate level greater social media use is found to be associated with a lower employee performance.

Among the mediating variables EE and TC are not significantly correlated (r = 0.04, ns), which is noteworthy because it suggests that they may capture distinct mechanisms rather than overlapping aspects of the same process. Both variables, however, show positive and significant correlations with EP: EE (r = 0.21, p < .001) and TC (r = 0.21, p < .001). This pattern provides preliminary support for the proposed mediation framework, where employee engagement and task completion may operate as independent pathways linking social media usage to employee performance. Also, the magnitude of the correlations is low to moderate and none of the coefficients approaches levels typically associated with multicollinearity concerns. The correlation analysis supports proceeding with structural modelling and analyses.

Non-response Bias Assessment

Non-response bias was assessed using the early-late respondent technique. Where the usable responses were ordered chronologically according to timestamp and from which first 25% of cases were classified as early respondents.

Table 3: Comparison of Early (first 25%) and Late (last 25%) respondents

Variable	Early Respondents (n = 177) M (SD)	Late Respondents (n = 177) M (SD)	t	p
SMU	3.21 (0.74)	3.27 (0.71)	-0.78	.437
EE	3.68 (0.69)	3.62 (0.73)	0.81	.419
TC	3.84 (0.58)	3.79 (0.61)	0.79	.431
EP	3.76 (0.63)	3.71 (0.66)	0.73	.466

While the last 25% were classified as late respondents. Independent-samples t tests were conducted to compare the two groups. As shown in Table 3 no statistically significant differences were observed between early and late respondents on any of the focal variables (p > .05). These results suggest that non-response bias is unlikely to have materially affected the findings.

Measurement Model (CFA) and Reliability

Before testing the structural relationships, the quality of the measurement model was assessed using CFA-based reliability and convergent validity indicators. Table 4 shows Cronbach's alpha, average variance extracted (AVE), the \sqrt{AVE} and composite reliability (CR, ρ_c) for all constructs.

The measurement model demonstrates strong internal consistency and satisfactory convergent validity for all constructs. Cronbach's alpha values range from 0.843 to 0.947 exceeding the commonly accepted threshold of 0.70 (Tavakol & Dennick, 2011) and indicating good to excellent reliability. Especially SMU ($\alpha = 0.947$) shows very high internal consistency while EE ($\alpha = 0.893$), TC ($\alpha = 0.887$) and EP shows ($\alpha = 0.843$) also demonstrate robust reliability. These values suggest that the items within each construct are measuring a coherent underlying concept. Composite reliability (CR) which estimates further support this conclusion. All CR values are well above the recommended cut-off of 0.70, ranging from 0.889 (EP) to 0.954 (SMU). Because CR is generally considered a more precise reliability estimate in SEM than Cronbach's alpha (as it accounts for standardized loadings), these results provide additional confidence that the latent constructs are measured with adequate precision.

Convergent validity is also supported where AVE values for all constructs exceed the recommended threshold of 0.50, with values of 0.614 SMU, 0.654 EE, 0.643 TC and 0.616 EP. This indicates that, on average, each construct explains more than 50% of the variance in its observed indicators, which is consistent with acceptable convergent validity. Notably, the AVE values for EE and TC are comparatively strong, suggesting that the retained indicators represent these latent variables well.

Table 4: Reliability and Convergent Validity (CFA-based) of constructs

Construct	Items (k)	Cronbach's alpha	AVE	sqrt(AVE)	CR (rho_c)
SMU	13	0.947	0.614	0.783	0.954
EE	6	0.893	0.654	0.809	0.919
TC	6	0.887	0.643	0.802	0.915
EP	5	0.843	0.616	0.785	0.889

The square root of AVE (\sqrt{AVE}) values are also relatively high (0.783 to 0.809), which is important for subsequent discriminant validity assessment Fornell-Larcker criterion (Fornell & Larcker, 1981). In practical terms, these values indicate that each construct shares substantial variance with its own indicators. When considered together with the reliability statistics, the evidence suggests that the constructs are both internally consistent and empirically well-defined. The CFA-based measurement assessment supports the adequacy of the scales used in this study and provides a sound basis for proceeding to structural model estimation and hypothesis testing.

CFA and Model Fit

The confirmatory factor analysis (CFA) (Brown, 2015) is done to test how well the measured variables represent a smaller number of unobserved latent constructs. The measurement model fits the observed data very well. As shown in Table 5, the chi-square statistic is $\chi^2(936) = 980.9$, $p = .15$, which is non-significant. A non-significant chi-square suggests that the discrepancy between the sample covariance matrix and the model-implied covariance matrix is not statistically meaningful. This is noteworthy because chi-square is highly sensitive to sample size and model complexity; therefore, obtaining a non-significant result in a model with 936 degrees of freedom provides strong evidence of good overall fit.

This conclusion is reinforced by the normed chi-square ($\chi^2/df = 1.048$) which is below conventional cutoffs and indicates a very small misfit relative to model complexity. In practical terms this suggests that the latent structure specified in the model reproduces the observed relationships among the indicators with high precision rather than fitting only in a broad or approximate sense.

The RMSEA = 0.008 further supports this interpretation and points to an almost negligible level of approximation error. More importantly, the 90% confidence interval for RMSEA [0.000, 0.014] is narrow and remains well below even conservative thresholds across its full range. This matters because the confidence interval provides information not only about point fit but also about the stability and precision of that estimate. Here, the interval suggests that the model fit is not simply acceptable by chance in this sample; rather, the degree of misfit is consistently minimal.

The incremental fit indices also show excellent performance. Both CFI (0.997) and TLI (0.997) are proving that the proposed measurement model offers a substantial improvement over a null independence model and does so with very little penalty for complexity. These values imply that the latent constructs and their indicators are specified in a way that is highly consistent with the empirical covariance structure. Similarly, NFI (0.948) and RFI (0.945) exceed recommended thresholds, providing additional support from relative fit perspectives.

Table 5: Model fit indices

Fit Index	Value	Guideline	Interpretation
χ^2 (CMIN)	980.958	Smaller values preferred	Acceptable chi-square given large df
df	936		Model degrees of freedom
p-value	0.15	> 0.05	Indicates good overall model fit
χ^2/df (CMIN/DF)	1.048	< 3.0 (preferably < 2.0)	Excellent model fit
RMSEA	0.008	< 0.08 (good), < 0.05 (excellent)	Excellent approximation fit
RMSEA 90% CI	[0.000, 0.014]	Narrow CI, upper < 0.08	Very strong model precision
CFI	0.997	≥ 0.90 (good), ≥ 0.95 (excellent)	Excellent comparative fit

TLI (NNFI)	0.997	≥ 0.90 (good), ≥ 0.95 (excellent)	Excellent incremental fit
NFI	0.948	≥ 0.90	Good model fit
RFI	0.945	≥ 0.90	Good relative fit

The fit indices present a coherent pattern: the measurement model is not merely acceptable but empirically strong fit criteria. The convergence of multiple fit indices across different families reduces the likelihood that the model appears well-fitting due to reliance on any single criterion.

Because respondents evaluated both their own workplace social media behaviour and their own performance, the study remains vulnerable to social desirability and self-enhancement effects. Employees may under-report counterproductive social media use and over-report their task completion or performance.

Assessment of Common Method Variance

As reported in Table 6 the first factor extracted in the unrotated principal component analysis accounted for 28.573% of the total variance, which is well below the commonly accepted threshold of 50% representing that no single factor dominates the covariance structure.

Table 6: Assessment of Common Method Variance

Test	Indicator	Result	Criterion	Interpretation
Harman’s single-factor test	First factor variance explained	28.573%	< 50%	No serious CMV concern
Common latent factor	Range of loading differences	.004 to .029	< .20	No substantial CMV effect

Furthermore, the CLF differences in standardized factor loadings between models with and without the common latent factor ranged from .004 to .029 which are substantially below the recommended cutoff of .20.

Structural Model Results

The results of the structural model analysis and tests the hypothesized relationships among workplace social media usage, employee engagement, task completion, and employee performance are depicted in this subsection. Path coefficients, significance levels and model fit indicators are examined to evaluate the direct, mediating, and moderating effects proposed in the conceptual framework.

Direct Effects

The estimated direct structural paths and the results of hypothesis testing for H1-H5 are presented in Table 7 The direct-effects shows a clear and theoretically meaningful pattern where the social media usage of employees is positively related to engagement of employees and task completions. While its direct association with employee performance is negative. At the same time both employee engagement and task completions are positively associated with performance, EP. This is important because social media use may generate both enabling and constraining effects in the workplace.

First, the results support the argument that social media usage is associated with beneficial intermediate work processes. Specifically, SMU has a significant positive effect on employee engagement ($\beta = 0.247, B = 0.245, SE = 0.040, C.R. = 6.107, p < .001$) supporting hypothesis H1. The greater use of social media is linked with higher employee engagement thus social media does help employees being socially connected, informed and psychologically involved in work-related interactions. Similarly, SMU has a significant positive effect on task completions done ($\beta = 0.196, B = 0.197, SE = 0.040, C.R. = 4.865, p < .001$) supporting H2. Although the magnitude of this effect is somewhat smaller than the SMU → EE path, it still indicates that social media usage is positively associated with employee’s ability to complete tasks.

Table 7: Direct Structural Paths and Hypothesis Testing

Hypothesis	Path	Sign	β (Std.)	B (Unstd.)	SE	C.R.	p	Decision
H1	SMU → EE	+	0.247	0.245	0.040	6.107	***	Supported
H2	SMU → TC	+	0.196	0.197	0.040	4.865	***	Supported

H3	EE → EP	+	0.257	0.254	0.042	5.974	***	Supported
H4	TC → EP	+	0.251	0.243	0.041	5.864	***	Supported
H5	SMU → EP	-	- 0.269	-0.260	0.040	- 8.195	***	Supported

Second, both proposed mediating variables show significant positive effects on employee performance. EE positively predicts EP ($\beta = 0.257, B = 0.254, SE = 0.042, C.R. = 5.974, p < .001$) supporting hypothesis H3 while TC also positively predicts performance ($\beta = 0.251, B = 0.243, SE = 0.041, C.R. = 5.864, p < .001$) supporting H4. The standardized coefficients for these two paths are very similar, which suggests that employee engagement and task completion contribute to performance in comparably meaningful ways within the present model. This is analytically useful because it supports the decision to treat them as parallel mechanisms rather than assuming one is clearly dominant.

Most notably, however, the model also shows a significant negative direct effect of SMU on EP ($\beta = -0.269, B = -0.260, SE = 0.040, C.R. = -8.195, p < .001$) supporting H5 (non-directional hypothesis). This finding indicates that, after accounting for the positive pathways in the model social media usage still retains a direct negative association with employee performance. In substantive terms, this suggests that social media use may simultaneously support engagement and task-related processes while also introducing costs such as distraction, attentional fragmentation, or interruptions that directly suppress performance.

Finally, the direct path results provide the foundation for the mediation analysis that follows. The presence of positive paths from SMU to EE & TC and from EE & TC to EP. A negative direct path from SMU to EP points to a complex effect structure in which social media usage is neither uniformly beneficial nor uniformly harmful. Instead, its influence on performance appears to operate through competing pathways, making mediation testing essential for understanding the net relationship.

MEDIATION RESULTS

The mediation results are where the model becomes especially meaningful, because they show how social media usage translates into employee performance rather than reducing the relationship to a single coefficient. As shown in Table 8, both proposed mediators employee engagement and task completions carry statistically significant indirect effects from SMU to EP and they do so in the expected positive direction. This provides strong support for the argument that social media usage can improve performance through specific organizational and behavioral mechanisms, even when its overall direct association with performance is not positive.

Table 8 Decomposition of Direct, Indirect and Total Effects of SMU on EP (Parallel Mediation via EE and TC)

Effect Type	Path	β (Std.)	95% Bootstrapped CI	p	Decision
Specific indirect effect	SMU → EE → EP	0.083	[0.059, 0.112]	< .001	Supported (H6)
Specific indirect effect	SMU → TC → EP	0.061	[0.038, 0.087]	< .001	Supported (H7)
Total indirect effect	SMU → (EE, TC) → EP	0.144	[0.109, 0.182]	< .001	Supported (H8)
Direct effect (c')	SMU → EP (controlling for EE and TC)	- 0.405	-	< .001	Significant
Total effect (c)	SMU → EP	- 0.261	[-0.328, -0.193]	< .001	Significant

First, the specific indirect effect through employee engagement is positive and significant ($\beta = 0.083, 95\%$ bootstrapped CI [0.059, 0.112], $p < .001$), supporting H6. Because the confidence interval does not include zero, the mediation effect is statistically reliable. Substantively, this suggests that one important way social media usage contributes to performance is by strengthening employee’s psychological connection to work likely through interaction, visibility, responsiveness and a stronger sense of involvement in work-related communication. In this model, engagement is not just an attitude sitting in the background; it functions as a real transmission mechanism linking digital behaviour to performance outcomes.

Second, the specific indirect effect through task completion is also positive and significant ($\beta = 0.061$, 95% bootstrapped CI [0.038, 0.087], $p < .001$), supporting H7. Again, the confidence interval excludes zero, confirming that the effect is robust. This finding is important because it captures the more behavioural side of the model: social media usage appears to support performance when it helps employees move work forward, coordinate tasks, or complete activities more efficiently. Although this indirect effect is somewhat smaller than the EE pathway, it remains substantively meaningful and clearly contributes to the broader explanation of how SMU relates to EP.

When the two mediators are considered together, the total indirect effect of SMU on EP is positive and significant ($\beta = 0.144$, 95% bootstrapped CI [0.109, 0.182], $p < .001$), supporting H8. This is a key result. It shows that, taken jointly, employee engagement and task completion form a meaningful parallel mechanism through which social media usage can enhance employee performance. In other words, the model demonstrates that social media is not simply a disruptive force. It also creates pathways that can improve performance when it increases engagement and supports task execution.

At the same time, the mediation results also reveal an important tension. The direct effect (c') of SMU on EP, after controlling for EE and TC, remains significant and negative ($\beta = -0.405$, $p < .001$) while the total effect (c) is also negative ($\beta = -0.261$, 95% CI [-0.328, -0.193], $p < .001$). The fact that the total effect is less negative than the direct effect reflects the positive indirect effects operating through EE and TC. Put differently, the mediation pathways partially offset the negative direct association between SMU and performance, but they do not fully reverse it.

This pattern is theoretically and practically important. It indicates a form of competitive (or inconsistent) mediation, where the indirect effects and direct effect operate in opposite directions. In the present study, social media usage appears to produce performance-supporting mechanisms (greater engagement and better task completion) while simultaneously retaining a performance-reducing direct effect a result that is fully consistent with the dual nature of social media in organizational life. It can facilitate communication and coordination, but it can also introduce distraction, attentional switching and interruption costs. The mediation analysis captures that complexity clearly and this is precisely why testing parallel mediators adds value to the paper.

Moderation Analysis (Interaction Effects)

The moderation test offers a useful clarification of the role of employee engagement in this model. While EE is clearly important for employee performance the results show that its role is primarily additive rather than interactive in relation to social media usage. As reported in Table 9 both SMU and EE have significant main effects on EP, but the interaction term $SMU \times EE$ is not significant meaning that EE contributes to performance directly, but it does not significantly change the strength of the SMU and EP relationship.

More specifically, the direct effect of SMU on EP is negative and statistically significant ($B = -0.397$, $SE = 0.034$, $C.R. = -11.509$, $p < .001$), indicating that higher social media usage is associated with lower employee performance in the moderation model. In contrast, EE has a positive and statistically significant effect on EP ($B = 0.390$, $SE = 0.034$, $C.R. = 11.349$, $p < .001$), showing that employees with higher engagement tend to report better performance. These two findings are substantively important on their own: they suggest that social media usage and employee engagement both matter for performance, but in opposite directions.

Table 9: Moderation of Employee Engagement on the Social Media Usage-Employee Performance Relationship

Predictor → Outcome	B	SE	C.R.	p	Decision
SMU → EP	-0.397	0.034	-11.509	< .001	Significant
EE → EP	0.390	0.034	11.349	< .001	Significant
$SMU \times EE \rightarrow EP$ (H9)	-0.006	0.033	-0.192	.848	Not Supported

However, the key test for moderation $SMU \times EE \rightarrow EP$ is not significant ($B = -0.006$, $SE = 0.033$, $C.R. = -0.192$, $p = .848$). Accordingly, H9 is not supported. The coefficient is not only statistically non-significant but also extremely small in magnitude, indicating that the interaction contributes virtually no explanatory value beyond the main effects. In practical terms, this means that the negative association between SMU and EP does not differ in a statistically reliable way across levels of employee engagement.

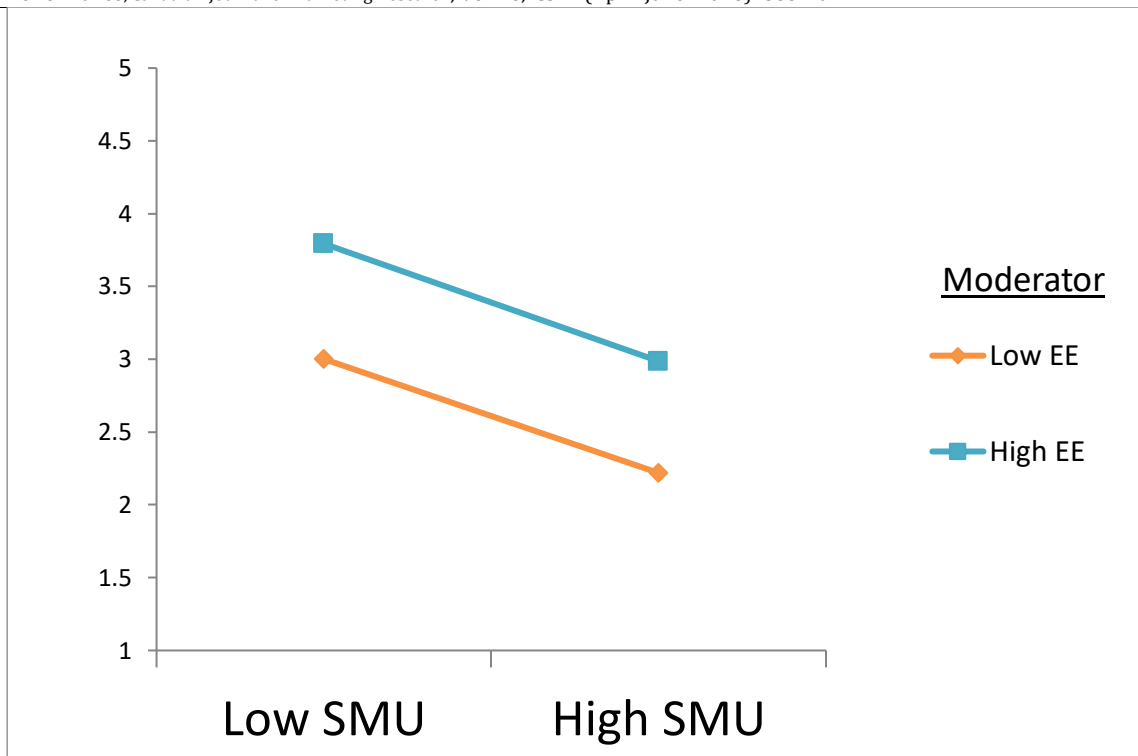


Figure 2: Two-way interaction graph showing impact of Employee Engagement as Moderator, EE strengthens the negative relationship between SMU and EP.

The interaction plot (Figure 2) is still useful for descriptive interpretation, but it should be read cautiously and always alongside the inferential test. Visually, the lines for low and high EE both slope downward from low SMU to high SMU, which is consistent with the negative main effect of SMU on EP. At the same time, the high-EE line remains above the low-EE line across both SMU conditions, reflecting the positive main effect of EE on performance. The small difference in slope between the two lines may create an impression of moderation, but the statistical test confirms that this apparent divergence is not robust. In other words, the graph mainly illustrates baseline performance differences by engagement level, not a reliable interaction effect.

Put differently, engagement helps employees perform better, yet it does not appear to change how strongly social media usage relates to performance outcomes. This distinction is important because it supports the study’s decision to treat EE as a meaningful mediator and direct predictor while showing that its hypothesized moderating role is not empirically supported. Although the plotted simple slopes appear visually different, the interaction coefficient was near zero and non-significant. Accordingly, the figure should be interpreted as illustrating the main effects of social media usage and employee engagement rather than a reliable moderation pattern.

RESULTS DISCUSSION

The results paint a nuanced picture of workplace social media use one that is much more informative than a simple “good” versus “bad” conclusion. Across the direct, mediation and moderation analyses, the pattern is consistent: social media usage is associated with both enabling mechanisms and performance costs. Specifically, SMU appears to support employee engagement and task completion and both of these variables, in turn, are positively related to employee performance. At the same time, SMU retains a significant negative direct effect on EP. This combination is not contradictory; rather, it reflects the dual nature of social media in organizational settings.

Discussion of Direct Effects (H1-H5)

The direct effects provide the first clear signal that social media use operates through multiple channels. The positive effects of SMU on EE (H1) and SMU on TC (H2) indicate that social media use is not merely a source of distraction in this sample. Employees who use social media more also report higher engagement and better task completion. This may reflect the role of social media in facilitating quick communication, informal support, task clarification and social connection within work routines.

The positive effects of EE on EP (H3) and TC on EP (H4) were also significant and their standardized coefficients were notably similar in magnitude. This is an important result because it shows that performance is shaped by both:

- A psychological route (engagement) and
- A behavioural execution route (task completion).

This balance strengthens the logic of the parallel mediation model. It suggests that performance is not driven only by how employees feel about their work or only by how efficiently they complete tasks; both matter and they matter in comparable ways.

At the same time, the direct path from SMU to EP (H5) is significant and negative. This is perhaps the most analytically interesting direct result because it implies that, even after accounting for positive organizational mechanisms, social media usage still carries a direct performance-reducing component. A plausible interpretation is that social media generates a mix of work-relevant utility and non-trivial cognitive costs (such as interruptions, attention switching, drift toward non-task content). This negative direct path is not a weakness of the model. It is one of its strongest contributions because it helps explain why prior studies often report mixed findings.

Discussion of Mediation Results (H6-H8)

The mediation results add depth to the interpretation by showing how SMU affects performance. Both specific indirect effects were positive and statistically significant:

- SMU → EE → EP (H6)
- SMU → TC → EP (H7)

This means that social media usage can improve employee performance indirectly by increasing engagement and by supporting task completion. These are not trivial pathways; they represent the mechanisms through which social media may become functionally useful in daily work. Among the two, the indirect pathway through employee engagement was somewhat stronger than the pathway through task completion. This suggests that the psychological dimension of social media use feeling connected, involved and engaged may be especially important in translating digital interaction into better performance outcomes. However, the task completion pathway was also meaningful and significant, reinforcing the argument that behavioural efficiency remains a central part of the process.

Most importantly, the total indirect effect (H8) was positive and significant, confirming that EE and TC jointly operate as a parallel mechanism linking SMU to EP. Yet this positive indirect effect coexists with a negative direct effect (*c'*) and a still-negative total effect (*c*). This pattern indicates competitive (inconsistent) mediation, where the indirect and direct effects move in opposite directions.

This is a particularly valuable finding for the paper because it provides a coherent explanation for apparently contradictory evidence in the literature. Social media use may simultaneously:
Support performance through engagement and task execution and

Harm performance through direct disruptive effects.

The model shows that the net impact of social media depends on which mechanisms dominate in a given context. That is exactly the kind of insight organizations need, because it shifts the conversation away from blanket assumptions and toward conditions and pathways.

Discussion of Moderation Results (H9)

The moderation analysis adds an important refinement to the role of employee engagement. While EE was expected to strengthen the relationship between SMU and EP the interaction term SMU × EE was not significant and H9 was not supported. This result suggests that EE does not function as a boundary condition in the hypothesized way. Put differently, employees with high engagement do perform better overall, but engagement does not significantly change how strongly social media usage relates to performance. This distinction matters. It indicates that EE is better understood in this model as:

A direct predictor of performance and

A mediating mechanism through which SMU can indirectly influence EP rather than as a moderator of the SMU - EP slope.

The interaction plot may visually suggest slight differences in slopes between low EE and high EE groups but the inferential test is decisive here: the apparent slope difference is not statistically reliable. This is a good example of why moderation should be interpreted primarily through the interaction coefficient rather than visual inspection alone.

Substantively, the non-significant moderation finding is still informative. It implies that engagement improves performance in a broad and consistent way, but it does not “shield” employees from the negative direct association between social media use and performance, nor does it amplify the positive side of SMU in a statistically detectable manner.

Table 10: Grid summary of the results obtained

Hypothesis	Path	Expected Direction	Empirical Result	Decision	Interpretation
H1	SMU → EE	+	Positive, significant	Supported	Higher SMU is associated with higher engagement
H2	SMU → TC	+	Positive, significant	Supported	Higher SMU is associated with better task completion
H3	EE → EP	+	Positive, significant	Supported	Engagement contributes positively to performance
H4	TC → EP	+	Positive, significant	Supported	Task completion contributes positively to performance
H5	SMU → EP	Significant (non-directional)	Negative, significant	Supported	SMU retains a direct negative effect on performance
H6	SMU → EE → EP	+ indirect	Positive, significant	Supported	Engagement mediates the SMU-EP relationship
H7	SMU → TC → EP	+ indirect	Positive, significant	Supported	Task completion mediates the SMU - EP relationship
H8	SMU → (EE, TC) → EP	+ total indirect	Positive, significant	Supported	Parallel mediation is supported
H9	SMU × EE → EP	+ interaction	Non-significant	Not Supported	EE does not moderate the SMU - EP relationship

The grid Table 10 makes the pattern very clear the model strongly supports the mediation framework, but not the moderation hypothesis. Results show that EE matters as a mechanism and direct predictor, but not as a conditional amplifier of SMU's effect on performance.

Concurrent validity Empirically, the concurrent validity pattern is substantively coherent. In the present study employee engagement and task completion were both positively related to EP at the bivariate level ($r = .21, p < .001$ for both), whereas social media usage was negatively related to EP ($r = -.24, p < .001$). In the structural model, the same criterion-related pattern remained evident the $EE \rightarrow EP$ ($\beta = .257, p < .001$) (Megdadi et al., 2023; Men et al., 2020) and $TC \rightarrow EP$ ($\beta = .251, p < .001$) were positive and significant while $SMU \rightarrow EP$ ($\beta = -.269, p < .001$) was negative and significant (Leftheriotis & Giannakos, 2014). The mediation decomposition further reinforced this pattern through significant positive indirect effects via EE ($\beta = .083, 95\% CI [.059, .112]$) and TC ($\beta = .061, 95\% CI [.038, .087]$) and a positive total indirect effect $\beta = .144, 95\% CI [.109, .182]$. These coefficients are modest but meaningful in applied behavioral research where correlation magnitudes in the .10–.30 range are considered practically informative (Indu et al., 2025).

The same criterion-related pattern is retained and strengthened conceptually at the structural model level. Both mediators remain positively associated with EP after simultaneous estimation ($EE \rightarrow EP: \beta = 0.257, p < .001$ $TC \rightarrow EP$ and $\beta = 0.251, p < .001$) (Kessler et al., 2003; Lysandra et al., 2023) while SMU retains a significant negative direct effect on EP (SMU

→ EP: $\beta = -0.269$, $p < .001$) and a negative total effect ($\beta = -0.261$, $p < .001$). This is an important validation point. The constructs do not merely correlate with EP in isolation they continue to relate to EP in theoretically interpretable ways when modelled together. In other words, the criterion relationships are not artefacts of simple pairwise association, but remain visible under a more demanding multivariate structure.

The mediation results further reinforce this concurrent criterion-related evidence. SMU shows positive specific indirect effects on EP through EE ($\beta = 0.083$, 95% CI [0.059, 0.112], $p < .001$) and TC ($\beta = 0.061$, 95% CI [0.038, 0.087], $p < .001$) and a positive total indirect effect ($\beta = 0.144$, 95% CI [0.109, 0.182], $p < .001$) (Leftheriotis & Giannakos, 2014; Megdadi et al., 2023). This decomposition is especially valuable for validity interpretation because it shows that the constructs are linked to the criterion employee performance.

Concurrent validity was supported by the criterion-related pattern of associations involving employee performance. Specifically, EE and TC were positively related to EP at both the bivariate and structural-model levels whereas SMU showed a negative direct association with EP. The fact that these theoretically expected relationships remained significant under simultaneous estimation provides evidence that the focal constructs demonstrate meaningful concurrent criterion-related validity with respect to performance of employees.

Theoretical Implications

The findings offer several theoretical implications for the literature on social media use and employee outcomes. The results show that social media usage is neither uniformly beneficial nor uniformly harmful. It simultaneously activates positive indirect pathways employee engagement and task completion while retaining a negative direct effect on employee performance. It Strengthens mechanism-based explanation by demonstrating significant mediation through employee engagement and task completion the study shifts the discussion from simple association to process explanation that is, how social media use influences performance. The study shows that psychological (engagement) and behavioural (task completion) mechanisms operate in parallel and both make meaningful contributions to performance. Employee engagement is supported as a direct predictor and mediator, but not as a moderator. This refines theory by suggesting that engagement contributes to performance primarily through its main and mediating effects, rather than by changing the strength of the SMU–EP relationship. The pattern of competitive and inconsistent mediation (positive indirect effects but negative direct effect) offers a strong theoretical explanation for why previous studies may report conflicting conclusions about workplace social media use.

Practical and Policy Implications for HEIs

For HEIs the findings suggest that social media should be managed strategically rather than treated as either a complete risk or a complete opportunity.

Practical Implications (Management) Since social media can improve engagement and task completion, strict prohibition may also block potentially productive uses. HEIs should encourage social media practices that support communication, coordination, academic administration and collaborative task execution. Institutions can introduce simple routines such as notification management, response-time norms and focused work windows to limit interruption-related productivity loss. Because EE has a strong positive effect on performance, HEIs should invest in communication climates and digital practices that improve employee involvement and connectedness. Practical Implications should include

First, Social media should not be treated as either wholly beneficial or wholly harmful. Instead, HEIs should manage it as a dual-purpose workplace tool which supports engagement of employees and enhances task completed if used appropriately. Social media can also reduce performance of employees if it becomes a source of distractions and attention fragmentation. This means that institutional responses should focus on guided use rather than blanket restriction.

From a managerial perspective, HEIs should encourage work related uses of social media to support communication and coordination. For example, departments may use approved digital channels for timetable updates, academic coordination, administrative announcements, rapid clarification of routine issues and team-based problem solving. At the same time, the managers should reduce the disruptive side of social media by enabling proper norms for message timing, response and notifications. Practices discouraging non urgent messaging during peak work hours and promoting boundary management can help limit interruptions. Since employee engagement showed a positive association with performance the HEIs should also use digital communication strategically to strengthen participation and connectedness among employees.

Policy Implications (Institutional-Level) policies should distinguish between work-related and non-work-related social media use rather than applying one broad rule to all usage. Different staff roles in HEIs (faculty, administrators, support staff) may require different social media use norms depending on task demands and communication intensity. HEIs can incorporate training on effective digital communication, attention management and responsible social media use into staff development programs.

HEIs should also develop policies which balance role sensitive social media guidelines rather than one uniform rule for all employees. In HEIs teaching and non-teaching staff perform different kinds of work and therefore require different norms regarding platform use. Institutional policy should distinguish between work related and non-work-related social media usage clarifying acceptable and non-acceptable usage during working hours and define expectations around responsiveness and professional conduct. Training programs on digital productivity and attention management would further help employees use social media more effectively while minimizing distraction related losses. Finally, HEIs should evaluate outcomes rather than focusing only on time spent on social media. In this way, institutions can move from a control-based approach to a performance oriented digital use strategy.

CONCLUSION, LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

This study examined how social media usage relates to employee performance by testing employee engagement and task completion as parallel mediators and employee engagement as a moderator. The findings show that social media usage has a complex and mixed relationship with employee performance: it is associated with a negative direct effect on performance, but also with positive indirect effects through employee engagement and task completion. Thus, social media usage appears to support performance through engagement and task execution mechanisms while simultaneously carrying direct performance costs.

While the study offers meaningful insights, several limitations should be acknowledged. The data were collected at one point in time which limits causal inference and prevents stronger conclusions about temporal ordering among SMU, EE, TC and EP. All constructs were measured using self-reports, which may introduce common method bias and social desirability effects. The findings are grounded in the higher education context and may not generalize fully to corporate, industrial, or public-sector settings with different task structures and digital norms. SMU was modelled as an overall construct; however, different forms of use (work-related vs. non-work-related, active vs. passive use) may have different effects on performance. The study examined employee engagement as a moderator, but other boundary conditions may better explain variation in the SMU - EP relationship. Future studies should test

- The model over time to better establish causality and examine how digital behaviour and performance evolve.
- Use of supervisor ratings, peer ratings and objective performance indicators would strengthen validity and reduce same-source bias.
- Replicating the model in non-HEI settings and across occupational groups would improve generalizability and reveal context-specific patterns.
- Variables such as digital distraction, technostress, job autonomy, role clarity, workload and organizational communication climate may provide deeper explanation.

REFERENCES

1. Ahmad, M., Ali, A., & Nawaz, H. (2024). Transforming Technology Adoption: How Social Media Communication Can Break Barriers in Public Organizations. In *Perspectives on Innovation and Technology Transfer in Managing Public Organizations* (pp. 249–267). IGI Global Scientific Publishing.
2. Ahmad, R., Nawaz, M. R., Ishaq, M. I., Khan, M. M., & Ashraf, H. A. (2023). Social exchange theory: Systematic review and future directions. *Frontiers in Psychology*, 13, 1015921.
3. Aragoncillo, L., & Orus, C. (2018). Impulse buying behaviour: An online-offline comparative and the impact of social media. *Spanish Journal of Marketing-ESIC*, 22(1), 42–62.
4. Auxier, B., & Anderson, M. (2021). Social media use in 2021. *Pew Research Center*, 1(1), 1–4.
5. Bakker, A. B., & Demerouti, E. (2007). The Job Demands-Resources model: State of the art. *Journal of Managerial Psychology*, 22(3), 309–328. (world). <https://doi.org/10.1108/02683940710733115>
6. Benn, S., Teo, S. T. T., & Martin, A. (2015). Employee participation and engagement in working for the environment. *Personnel Review*, 44(4), 492–510. (world). <https://doi.org/10.1108/PR-10-2013-0179>
7. Brown, T. A. (2015). *Confirmatory factor analysis for applied research*. Guilford publications.
8. Celebi, N., Liu, Q., & Karatoprak, M. (2022). A Survey of Deep Fake Detection for Trial Courts.
9. Chatterjee, S., Chaudhuri, R., Vrontis, D., & Giovando, G. (2023). Digital workplace and organization performance: Moderating role of digital leadership capability. *Journal of Innovation & Knowledge*, 8(1), 100334. <https://doi.org/10.1016/j.jik.2023.100334>
10. Corbeanu, A., & Iliescu, D. (2023). The Link Between Work Engagement and Job Performance. *Journal of Personnel Psychology*, 22, 111–122. <https://doi.org/10.1027/1866-5888/a000316>
11. Damayanti, T. A. (2023). The effect of social media quality, social media quantity, social media credibility and E-Wom on revisit intention: Destination brand awareness and destination satisfaction as intervening variables. *Calitatea*, 24(196), 87–97.
12. Eliyana, A., Ajija, S. R., Sridadi, A. R., Setyawati, A., & Emur, A. P. (2020). Information Overload and Communication Overload on Social Media Exhaustion and Job Performance. *Systematic Reviews in Pharmacy*,

- 11(8).
13. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50.
 14. Gallup Inc. (2023). Gallup's Q12 Employee Engagement Survey Gallup. Gallup.Com. <https://www.gallup.com/workplace/356063/gallup-q12-employee-engagement-survey.aspx>
 15. Gomez, R., Zarate ,Daniel, Brown ,Taylor, Hein ,Kaiden, & and Stavropoulos, V. (2024). The Bergen–Social Media Addiction Scale (BSMAS): Longitudinal measurement invariance across a two-year interval. *Clinical Psychologist*, 28(2), 185–194. <https://doi.org/10.1080/13284207.2024.2341816>
 16. Halbesleben, J. R., Neveu, J.-P., Paustian-Underdahl, S. C., & Westman, M. (2014). Getting to the “COR” understanding the role of resources in conservation of resources theory. *Journal of Management*, 40(5), 1334–1364.
 17. Indu, P. V., Vidhukumar, K., Chacko, D., Menon, V., Grover, S., & Gupta, S. (2025). Criterion validity, construct validity and factor analysis: An introductory overview. *Indian Journal of Psychiatry*, 67(9), 916–921. https://doi.org/10.4103/indianjpsychiatry_911_25
 18. Jiang, Y. (2021). Problematic Social Media Usage and Anxiety Among University Students During the COVID-19 Pandemic: The Mediating Role of Psychological Capital and the Moderating Role of Academic Burnout. *Frontiers in Psychology*, 12. <https://doi.org/10.3389/fpsyg.2021.612007>
 19. Jong, D., Chen, S.-C., Ruangkanjanases, A., & Chang, Y.-H. (2021). The Impact of Social Media Usage on Work Efficiency: The Perspectives of Media Synchronicity and Gratifications. *Frontiers in Psychology*, 12, 693183. <https://doi.org/10.3389/fpsyg.2021.693183>
 20. Karimi, R., Baghalzadeh Shishehgharkhaneh, M., Moehler, R. C., & Fang, Y. (2024). Exploring the Impact of Social Media Use on Team Feedback and Team Performance in Construction Projects: A Systematic Literature Review. *Buildings*, 14(2), Article 2. <https://doi.org/10.3390/buildings14020528>
 21. Kasim, N. M., Fauzi, M. A., Wider, W., & Yusuf, M. F. (2022). Understanding Social Media Usage at Work from the Perspective of Social Capital Theory. *Administrative Sciences*, 12(4). <https://doi.org/10.3390/admsci12040170>
 22. Kessler, R. C., Barber, C., Beck, A., Berglund, P., Cleary, P. D., McKenas, D., Pronk, N., Simon, G., Stang, P., Ustun, T. B., & Wang, P. (2003). The World Health Organization Health and Work Performance Questionnaire (HPQ). *Journal of Occupational and Environmental Medicine*, 45(2), 156–174. <https://doi.org/10.1097/01.jom.0000052967.43131.51>
 23. Koessmeier, C., & Büttner, O. B. (2021). Why Are We Distracted by Social Media? Distraction Situations and Strategies, Reasons for Distraction and Individual Differences. *Frontiers in Psychology*, 12. <https://doi.org/10.3389/fpsyg.2021.711416>
 24. Koopmans, L., Bernaards, Hildebrandt, Buuren, V., Beek, V. D., & Vet, D. (2013). Improving the individual work performance questionnaire using rasch analysis. *Occupational and Environmental Medicine*, 70(Suppl 1), A17.3-A18. <https://doi.org/10.1136/oemed-2013-101717.51>
 25. Landers, R. N., & Callan, R. C. (2014). Validation of the Beneficial and Harmful Work-Related Social Media Behavioral Taxonomies: Development of the Work-Related Social Media Questionnaire. *Soc. Sci. Comput. Rev.*, 32(5), 628–646. <https://doi.org/10.1177/0894439314524891>
 26. Leftheriotis, I., & Giannakos, M. N. (2014). Using social media for work: Losing your time or improving your work? *Computers in Human Behavior*, 31, 134–142. <https://doi.org/10.1016/j.chb.2013.10.016>
 27. Lysandra, C. L., Noermijati, N., & Kurniawati, D. T. (2023). Improving Employee Performance Through the Use of Social Media At the Workplace: Mediated By Employee Engagement and Job Satisfaction. *Jurnal Aplikasi Manajemen*, 21(2), 393–403.
 28. MA, Y., ZHAO, X., HE, X., & REN, L. (2022). The impact of social media on executive functions: Beneficial or harmful? *Advances in Psychological Science*, 30(2), 406.
 29. Marengo, D., Poletti, I., & Settanni, M. (2020). The interplay between neuroticism, extraversion and social media addiction in young adult Facebook users: Testing the mediating role of online activity using objective data. *Addictive Behaviors*, 102, 106150. <https://doi.org/10.1016/j.addbeh.2019.106150>
 30. Mauno, S., Kinnunen, U., & Ruokolainen, M. (2007). Job demands and resources as antecedents of work engagement: A longitudinal study. *Journal of Vocational Behavior*, 70(1), 149–171. <https://doi.org/10.1016/j.jvb.2006.09.002>
 31. Megdadi, Y., Jumaa, M. H. A., Alghizzawi, M., Megdad, Z., Tahat, D. N., Tahat, K., & Habes, M. (2023). The effect of social media on improving the recruitment process: Regional commercial bank's employee engagement as a mediator. 1–7.
 32. Men, L. R., O'Neil, J., & Ewing, M. (2020). Examining the effects of internal social media usage on employee engagement. *Public Relations Review*, 46(2), 101880.
 33. Mohiya, M. (2025). The effect of social media on employee engagement: The mediating role of job satisfaction and perceived organizational support. *Humanities and Social Sciences Communications*, 12(1), 1–15. <https://doi.org/10.1057/s41599-025-04849-1>
 34. Neuber, L., Englitz, C., Schulte, N., Forthmann, B., & Holling, H. (2022). How work engagement relates to performance and absenteeism: A meta-analysis. *European Journal of Work and Organizational Psychology*. (world). <https://www.tandfonline.com/doi/abs/10.1080/1359432X.2021.1953989>
-

35. Ohly, S., & Bastin, L. (2023). Effects of task interruptions caused by notifications from communication applications on strain and performance. *Journal of Occupational Health*, 65(1), e12408. <https://doi.org/10.1002/1348-9585.12408>
36. Oksa, R., Pirkkalainen, H., Salo, M., Savela, N., & Oksanen, A. (2022). Professional social media-enabled productivity: A five-wave longitudinal study on the role of professional social media invasion, work engagement and work exhaustion. *Information Technology & People*, 35(8), 349–368. <https://doi.org/10.1108/ITP-11-2021-0899>
37. Pekkala, K., & van Zoonen, W. (2022). Work-related social media use: The mediating role of social media communication self-efficacy. *European Management Journal*, 40(1), 67–76. <https://doi.org/10.1016/j.emj.2021.03.004>
38. Sarah Chanu, H. (2025). Impact Of Social Media On Employee Productivity And Workplace Behaviour.
39. Schaufeli, W. B., Bakker, A. B., & Salanova, M. (2006). The Measurement of Work Engagement With a Short Questionnaire: A Cross-National Study. *Educational and Psychological Measurement*, 66(4), 701–716. <https://doi.org/10.1177/0013164405282471>
40. Schaufeli, W. B., Salanova, M., González-romá, V., & Bakker, A. B. (2002). The Measurement of Engagement and Burnout: A Two Sample Confirmatory Factor Analytic Approach. *Journal of Happiness Studies*, 3(1), 71–92. <https://doi.org/10.1023/A:1015630930326>
41. Scholze, A., & Hecker, A. (2024). The job demands-resources model as a theoretical lens for the bright and dark side of digitization. *Computers in Human Behavior*, 155, 108177. <https://doi.org/10.1016/j.chb.2024.108177>
42. Sharma, M. K., John, N., & Sahu, M. (2020). Influence of social media on mental health: A systematic review. *Current Opinion in Psychiatry*, 33(5), 467–475.
43. Sivakumar, A., Jayasingh, S., & Shaik, S. (2023). Social media influence on student’s knowledge sharing and learning: An empirical study. *Education Sciences*, 13(7), 745.
44. Soane, E., Truss, C., Alfes, K., Shantz, A., Rees, C., & Gatenby, M. (2012). Development and application of a new measure of employee engagement: The ISA Engagement Scale. *Human Resource Development International*, 15(5), 529–547. <https://doi.org/10.1080/13678868.2012.726542>
45. Song, Q., Wang, Y., Chen, Y., Benitez, J., & Hu, J. (2019). Impact of the usage of social media in the workplace on team and employee performance. *Information & Management*, 56(8), 103160.
46. Sun, Y., Ding, Z., & Zhang, Z. (2020). Enterprise social media in workplace: Innovative use cases in China. *IEEE Transactions on Engineering Management*, 70(7), 2447–2462.
47. Tandon, A., Dhir, A., Almugren, I., AlNemer, G. N., & M?ntym?ki, M. (2021). Fear of missing out (FoMO) among social media users: A systematic literature review, synthesis and framework for future research. *Internet Research*, 31(3), 782–821.
48. Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach’s alpha. *International Journal of Medical Education*, 2, 53.
49. Tuck, A. B., & Thompson, R. J. (2024). The Social Media Use Scale: Development and Validation.
50. Upshaw, J. D., Stevens, C. E., Ganis, G., & Zabelina, D. L. (2022). The hidden cost of a smartphone: The effects of smartphone notifications on cognitive control from a behavioral and electrophysiological perspective. *PLOS ONE*, 17(11), e0277220. <https://doi.org/10.1371/journal.pone.0277220>
51. Valenti, G. D., Craparo, G., & Faraci, P. (2025). The Development of a Short Version of the Internet Addiction Test: The IAT-7. *International Journal of Mental Health and Addiction*, 23(2), 1028–1053. <https://doi.org/10.1007/s11469-023-01153-4>
52. van Zyl, L. E., Klibert, J., Shankland, R., Stavros, J., Cole, M., Verger, N. B., Rothmann, S., Cho, V., Feng, K., See-To, E. W. K., Roll, L. C., Ghosh, A., Arijs, D., & Glinska-Neweś, A. (2024). The academic task performance scale: Psychometric properties and measurement invariance across ages, genders and nations. *Frontiers in Education*, 9. <https://doi.org/10.3389/educ.2024.1281859>
53. Wegmann, E., Stodt, B., & Brand, M. (2015). Addictive use of social networking sites can be explained by the interaction of Internet use expectancies, Internet literacy and psychopathological symptoms. *Journal of Behavioral Addictions*, 4(3), 155–162. <https://doi.org/10.1556/2006.4.2015.021>
54. Wei, Z., Guo, Y., Tsang, M. H. L., Montag, C., Becker, B., & Kou, J. (2024). Social media distractions alter behavioral and neural patterns to global-local attention: The moderation effect of fear of missing out. *Computers in Human Behavior*, 157, 108258. <https://doi.org/10.1016/j.chb.2024.108258>
55. Williams, L. J., & Anderson, S. E. (1991). Job Satisfaction and Organizational Commitment as Predictors of Organizational Citizenship and In-Role Behaviors. *Journal of Management*, 17(3), 601–617. <https://doi.org/10.1177/014920639101700305>
56. Yen, Y.-S., Chen, M.-C., & Su, C.-H. (2020). Social capital affects job performance through social media. *Industrial Management & Data Systems*, 120(5), 903–922.
57. Zahrah, N., Hamid, S. N. B. A., Rani, S. H. B. A., & Kamil, B. A. B. M. (2017). The Mediating Effect of Work Engagement on The Relationship Between Islamic Religiosity and Job Performance. *Global Business & Management Research*, 9.
58. Zarate, D., Hobson, B. A., March, E., Griffiths, M. D., & Stavropoulos, V. (2023). Psychometric properties of the Bergen Social Media Addiction Scale: An analysis using item response theory. *Addictive Behaviors Reports*, 17, 100473. <https://doi.org/10.1016/j.abrep.2022.100473>

59. Zhao, X. (2021). Single Image Dehazing Using Bounded Channel Difference Prior. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) Workshops, 727–735.